International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-2, December 2019

Synthesis Algorithms for Adaptive Process Control Systems Based on Associative Memory Technology

Oripjon Olimovich Zaripov, Dildora Usmonovna Sevinova, Iskandar Uchqun ogli Sevinov

Abstract: ***The results of the regular synthesis algorithms development for adaptive process control systems based on the associative memory technology are presented in the article. The single-step and multi-step, deterministic and stochastic algorithms used for solving control and tracking problems are considered. The relative simplicity of these algorithms makes possible to recommend them for managing complex objects in conditions of uncertainty using concepts and associative memory technology. Based on the technology of associative memory, synthesis algorithms for adaptive production process control systems are proposed to function under unpredictable uncertainties and ensure the rate of the structure adapting process of the main system circuit, commensurate with the rate of transients in the technological control object operating under stochastic independent disturbances.***

Keywords: ***intelligent control system, associative memory, control object, adaptive control system.***

I. INTRODUCTION

The new technology development imposes increasingly stringent requirements on the operation quality of the control systems, which improvement by means of the innovative actuators gives a certain positive effect. However, a significant part of the problems - such as performance improvement, invariance to external influences, changes in the characteristics of the control object, etc., are not effectively solved by this approach. Therefore, an urgent need has arisen for improving management systems using non-traditional management technologies [1,3].

Revised Manuscript Received on December 30, 2019.
* Correspondence Author

Zaripov Oripjon Olimovich*, Doctor of Technical Sciences, Professor, Department of Information Processing and Control Systems, Tashkent State Technical University Named After Islam Karimov, Tashkent, Uzbekistan, uz3121@gmail.com.

Sevinova Dildora Usmonovna, Assistant, Department of Mechatronics and Robotics, Tashkent State Technical University Named After Islam Karimov, Tashkent, Uzbekistan.

Sevinov Iskandar Uchqun ogli, Magistrate, Department of Information Processing and Control Systems, Tashkent State Technical University named after Islam Karimov, Tashkent, Uzbekistan.

It is proposed to use control systems with associative memory to solve this problem. Associative memory technology, which has become very widespread in computer technology, is one of the alternative approaches to creating high-speed intelligent control systems. On the one hand this technology is based on the mechanisms of associative recording and information recovery, allowing access to data at high speed. This aspect of application has traditionally been studied in the field of computer technology [1-4]. On the other hand, the technology of associative memory allows to classify the state of the system at a qualitative level and to form controls that correspond to the current state of the system and a given criterion of control quality on the basis of associative connections. This aspect of the associative memory use is not practically studied. The main advantage of associative memory is the simplicity of the software and hardware implementations, which provides high performance, determined by the time of a separate memory cell access.

From the analysis of the complex dynamic system motion equation, it can be concluded that under unpredictable uncertainties, the behavior of the state vector is not known in advance, dynamic models for the synthesis of control laws turn out to be too complicated to implement. One of the ways to organize adaptive control in real time is the use of control systems with associative memory [5]. Traditionally, adaptive systems include self-tuning systems [6–9], which are divided into search and non-search. If the time required to determine the conditions of the extremum is not critical, for example, to control slow processes, then search methods are used [10]. The fastest are the non-search self-tuning systems [11], based on compensation approaches, the analytical determination of the extremum of the quality functional, which allows one to obtain the rate of the adaptation process commensurate with the rate of transient processes in the system. In type II intelligent control systems with associative memory, adaptive control is implemented on the basis of the possible dynamic states of the system and control laws' study that provide a set control goal.

II. PROPOSED METHODOLOGY

Synthesis of the control systems significantly complicates taking into account the control object inertia in dynamic objects and the main changes concern the structure of the main system circuit. Based on the main contour structure and the type of control goal, it is advisable to distinguish two classes of tasks. The first class is the control problem in transient, dynamic modes (the tracking problem), in which the control goal is associated with the exact processing of a changing setting action.

In such problems, the control goal is most conveniently set using the reference model - an auxiliary system that defines the desired transients in a closed system. The second class is control tasks in steady-state modes (control task), when the driving influence is constant and the main task of the system is to suppress the action of disturbances. In such systems, it is natural to set control goals that provide optimal suppression of disturbances, and use optimal controllers in the main circuit.

Since the both approaches are widely covered in the literature [8, 12], let's limit with one rather typical example of the adaptive control systems of each class and consider the possibilities of associative memory technology use in them.

It should be noted that the quality management task is reduced to training on the most complete set of possible states of the control object. According to the input vector containing data on the object state and the input impact, associative memory forms a control effect on the object.

A. Task statement

At first, consider control object description that is the same for both tasks. It is convenient to describe the linear discrete dynamic control object by the input-output equations, including directly observable outputs and having the form:

$$A\left(q^{-1}\right)y_{k+1} = B\left(q^{-1}\right)u_k + C\left(q^{-1}\right)\varphi_r ,$$

where $A(\cdot), B(\cdot), C(\cdot)$ - polynomials, q^{-1} - is the one-step delay operator $\left(q^{-1}x_k = x_{k-1}\right)$:

$$A(\lambda) = 1 + a_1\lambda + ... + a_n\lambda^n ,$$

$$B(\lambda) = 1 + b_1\lambda + ... + b_n\lambda^n ,$$

$$C(\lambda) = 1 + c_1\lambda + ... + c_n\lambda^n .$$

The coefficients of the polynomials *A*, *B*, *C* are considered unknown: $\xi = col\left(a_1,..., a_n, b_1,..., b_n, c_1,..., c_n\right)$, with $b_p \neq 0$, (i.e., the value of the delay p is unknown).

B. Discussion

In transient modes, disturbance is more caused by the inaccuracy of the control object model than by random external influences. Therefore, we assume that the perturbations are deterministic, and for the synthesis of the adaptation algorithm, we use the recurrent target inequality method. For a system with a reference model and the purpose of the tracking type control, the direct and identification approaches lead to equivalent structures. Let it be the driving force. We introduce the residual function:

$$\delta_k = G\left(q^{-1}\right)y_{k+1} - D\left(q^{-1}\right)r_k , \tag{1}$$

where $G(\cdot), D(\cdot)$ are given polynomials. If $\delta_k = 0$, then the movement of the control object is subjected to the equation of the reference model:

$$G\left(q^{-1}\right)y_{k+1} = D\left(q^{-1}\right)r_k . \tag{2}$$

C. Law of regulation

We choose the linear law of regulation in the main circuit:

$$u_k = \theta_k^T z_k , \tag{3}$$

where

$$z_k = col\left(y_k,..., y_{k-n+1}, u_{k-p},..., u_{k-m}, D\left(q^{-1}\right)r_k\right),$$

$$\theta_k = col\left(\theta_k^{(1)},..., \theta_k^{(n+m-p+2)}\right).$$

In this case, $\theta_* \in \Xi$ will exist such that, at $\theta_k = 0$, the equations of the closed-loop system (1), (3) coincide with the reference model up to an interference of $C\left(q^{-1}\right)\varphi_k$.

D. Adaptation algorithm

We take the adaptation algorithm in the form:

$$\theta_k = \begin{cases} \theta_k - \gamma \dfrac{\delta_k}{\left\|z_k\right\|} z_k , & \text{at } \left|\delta_k\right| > \Delta, \\ \theta_k , & \text{at } \left|\delta_k\right| \leq \Delta. \end{cases}$$

for the objective function $Q_k = \left|\delta_k\right|$ and with δ_k types (2).

E. Optimal control

We now consider an adaptive optimal control system for the case of stochastic independent disturbances φ_k with properties $M\varphi_k^4 < \infty$. As the control goal, we choose

$$\lim_{k\to\infty} \frac{1}{k}\sum_{i=1}^{k}\left|y_i\right|^2 \leq I_* , \tag{4}$$

where

$$I_* = \inf_{U_D} \lim_{k\to\infty} \frac{1}{k}\sum_{i=1}^{k}\left|y_i\right|^2 .$$

U_D there are many admissible control laws (non-proactive strategies) for which the upper limit on the left-hand side of (4) is finite. The desired adaptive strategy should be acceptable and, in addition, should not depend on the vector of the control object parameters: $\xi = col\left(a_1,..., b_1,..., c_{1,...}\right)$.

It is well known [9,13], if a control object (1) is minimal-phase, then there exists an optimal control law that is linear and described by the equation:

$$\alpha\left(q^{-1}\right)u_k = \beta\left(q^{-1}\right)y_k ,$$

where the coefficients of polynomials $\alpha(\lambda)$, $\beta(\lambda)$ are sought from the polynomial equation [8,14].

Retrieval Number: A4745119119/2019©BEIESP
DOI: 10.35940/ijitee.A4745.129219
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Taking the identification approach to the adaptive control systems construction, we will set the control law at the *k*-th step by the ratio:

$$B_k\left(q^{-1}\right)F_k\left(q^{-1}\right)u_k = q^{-p}G_k\left(q^{-1}\right)y_k + e_k, \qquad (5)$$

where polynomials $F_k(\lambda)$, $G_k(\lambda)$ are searched from the equations:

$$A_k(\lambda)F_k(\lambda) - \lambda^p C_k(\lambda) = G(\lambda),$$

$A_k(\lambda)$, $B_k(\lambda)$, $C_k(\lambda)$ - are the current polynomial estimates in the description of the control object (5), and $\{e_k\}$ - is the “test” disturbing process, independent of process $\{\varphi_k\}$ and having the properties:

$$Me_k = 0, \quad \lim_{k\to\infty} M|e_k|^4 = 0.$$

To complete the synthesis of adaptive control systems, it is left to specify an adaptation algorithm: constructing a vector θ_k of current estimate coefficients of polynomials $A_k(\lambda), B_k(\lambda), C_k(\lambda)$. The desired algorithm must have an identifying property: ensure convergence $\theta_k \overset{п.н.}{\to} \xi$.

To develop the adaptation algorithm, we introduce the notation: $w_{k-1} = col(-y_k,\dots,-y_{k-n},u_k,\dots,u_{k-n},\tilde{\varphi}_k,\dots,\tilde{\varphi}_{k-r})$, and we bring the control object equation (5) to the “update” form:

$$y_{k+1} = w_k^T\xi + \left[C\left(q^{-1}\right)-1\right]\left[\varphi_{k+1} - \tilde{\varphi}_{k+1}\right] + \varphi_{k+1},$$

convenient for the predictive model of the control object. Next, we construct random variables $\tilde{\varphi}_k$, interpreted as estimates of perturbations φ_k. As an adaptation algorithm, we choose a variant of the projection algorithm of stochastic approximation:

$$\theta_{k+1} = \mathrm{Pr}_{\Xi}\left\{\theta_k + \gamma_k w_k\left(y_{k+1} - w_k^T\theta_k\right)\right\}.$$

$$\gamma_{k+1}^{-1} = \gamma_k^{-1} + \left\|w_k\right\|^2 + 1, \quad \gamma_0 = 1,$$

$$\tilde{\varphi}_k = y_k - w_{k-1}T\left[\theta_{k-1} + \gamma_{k-1}w_{k-1}\left(y_k - w_{k-1}^T\theta_{k-1}\right)\right].$$

F. Implementing associative memory

Consider the possibility of implementing associative memory in such systems and the mechanism of associative sampling of the desired control vector.

The set of $U = \{u_1, u_2, \dots, u_m\}$ admissible controls for a complex object embedded in associative memory is finite. We assume that the control object is described by equation

$$y_k = f(u_k, r_k, \xi) + \varphi_k,$$

where $u_k \in R^m$ is the control action, $r_k \in R^s$ - is the measured disturbance, $\varphi_k \in R^l$ - is the measured output of the control object (the values of variables at time t_k are index k) $\xi \in \Xi \subset R^N$ - is a finite-dimensional vector of unknown parameters, Ξ - is a known convex set .

Let the output of the control object be a scalar quantity that has the meaning of a control quality indicator, and when choosing at the *k*-th step $u_k = v_j$, the output value $y_k = q_j + \varphi_k$ is measured, where q_i is the value of the “losses” when choosing control v_j, φ_k is an unknown disturbance or measurement interference.

Then it is possible to set a control goal:

$$y_k < \Delta, \text{ at } k < k_*$$

(in the case of deterministic φ_k) or

$$\frac{1}{k}\sum_{i=1}^{k} y_i < \Delta, \text{ at } k > k_*, \qquad (6)$$

$$My_k < \Delta, \text{ at } k > k_*,$$

(in the case of stochastic φ_k). If you set $\Delta = q_* + \Delta_q$, where $q_* = \min q_i$, then you can interpret the goals as minimizing with a given accuracy the losses measured at the *k*-th step with an error of φ_k. So, the task of associative memory consists in the optimal choice of a finite number of possible options under conditions of uncertainty.

We consider the interference random, then a single search may not be enough; repetition of tests, accumulation and averaging of results can improve the accuracy of optimization, i.e. achieve more difficult goals. Associative memory makes it possible to make multiple sorting directed: more often choose those actions that give less loss. This reduces the total number of tests required to achieve a given accuracy.

Let us consider two approaches to the synthesis of adaptive control systems for a finite stochastic object using associative memory technology [15]. We will describe the first approach in the case of binary losses, when only two binary values take the control object output, for example, $y_л$=0 (success) and $y_л$=1 (failure).

If $M\varphi_k = 0$, then $q_j = M\{y_k : u_k = v_j\}$ - is the probability of failure during the *j*-th action. The control algorithm is represented by a finite deterministic automaton, to the input of which y_k is fed, and the states are divided into *m* subsets (branches) of *n* states, and in states from the *j*-th branch, the automaton selects the *j*-th action, calculating by moving along the branch the number of failures that go contract.

The transition function of the automaton is designed so that the transition to the states of another branch occurs after n failures in a row.

It is easy to understand that such an automaton often selects the action with a greater chance of success. By increasing the "memory depth" (i.e., the number n), one can achieve an arbitrarily small asymptotic (at $k \to \infty$) error:

$$e_k = \frac{1}{k}\sum_{i=1}^{k} y_k - q_* ,$$

i.e. provide suboptimality of the system.

Another approach is the use of randomized algorithms defined by stochastic automata. The state of such an automaton is a probability vector:

$$P_k = col\left(p_k^{(1)},\dots, p_k^{(m)}\right),$$

where $p_k^{(j)} \geq 0$, $\sum_{j=1}^{m} p_k^{(j)} = 1$, and $p_k^{(j)}$ makes sense of the probability of choosing the j-th action at the k-th step.

Depending on the observed value of y_k, the probability $p_k^{(j)}$ is recalculated so as to increase the likelihood of the action that cause less loss. In the adaptive system language, the random action selection mechanism corresponds to a controller, the tunable parameters of which are set by the vector p_k.

The functioning of associative memory, based on adaptation algorithm p_k, can be constructed from the condition of an average decrease of some function associated with losses. Following [16], we describe one of such algorithms, the so-called projection algorithm, which does not require binary losses. The recount rule p_k has the form:

$$p_{k+1} = P_{r\Xi_k}\left\{p_k + \gamma_k \frac{y_k - \delta}{e(u_k)^T p_k} e(u_k)\right\}, \qquad (7)$$

where $\Xi_k = s_{\varepsilon k}$, $S_\varepsilon = \left\{ p \in R^m : \sum_{j=1}^{m} p(j) = 1,\ p^{(j)} \geq \varepsilon \right\}$ - is the "narrowed" simplex, $e(u_k)$ - is the m-dimensional vector whose j-th component is 1 if $u_k = v_j$ is zero otherwise; δ, $\{\varepsilon_k\}, \{\gamma_k\}$ - algorithm parameters. Let $M\varphi_k = 0$, i.e. $q_i = My_k$. The averaging expression Δp_k is proportional to the gradient of average losses

$$Q(p) = \sum_{j=1}^{m} q_j p^{(j)},$$

and $My_k = MQ(p_k)$.

Given inequalities

$$(Q(p) - q_*)^2 \leq \|p - p_*\|^2 \sum_{j \neq j_*} (q_j - q_*)^2,$$

we can conclude that the algorithm (7) ensures the speed of achieving the control goal (5) of order $1/\sqrt[3]{k}$. Achieving the control goal also occurs with non-uniqueness $\min_j q_j$.

III. RESULT ANALYSIS

As for other recurrence algorithms, the desire to ensure convergence (7) to an extremum point slows down the convergence rate of the algorithm. If constant steps are taken in (7), then we can obtain exponential estimates of the rate of convergence, but not to the "point", but to the "region".

The described control systems with associative memory have the following advantages:

- control can be carried out in one circuit at once according to several parameters;
- one associative memory can work simultaneously with several control loops, including different levels of management.

In the discrete adaptive control, several different methods and approaches compete. We have considered the single-step and multi-step, deterministic and stochastic algorithms that were used to solve control and tracking problems. The relative simplicity of these algorithms makes possible to recommend them for managing complex objects in uncertainty conditions using concepts and associative memory technology.

IV. CONCLUSION

Thus, on the basis of associative memory technology, algorithms for the synthesis of adaptive production process control systems have been proposed that are designed to function under unpredictable uncertainties and ensure the adaptation rate of the main system circuit structure, commensurate with the rate of transients in the technological control object, operating under stochastic independent disturbances.

REFERENCES

1. Чекинов Г.П., Кулялица А.Л., Бондаренко В.В. Применение ситуационного управления в информационной поддержке принятия решений при проектировании организационно - технических систем // Информационные технологии в проектировании и производстве. №2, 2003.
2. Забихифар С. Адаптивное управление робототехническими системами с использованием нейронных сетей и скользящих режимов. Диссертация на соискание ученой степени кан.технич.наук. Москва. 2018. -143 с.
3. Ajoudani, A., Zanchettin, A. M., Ivaldi, S., Albu-Schäffer, A., Kosuge, K., and Khatib, O. (2018). Progress and prospects of the human–robot collaboration. Auton. Robots 42, 957–975. doi: 10.1007/s10514-017-9677-2
4. Arimoto, S. (1990). Learning control theory for robotic motion. Int. J. Adapt. Control Signal Process. 4, 543–564. doi: 10.1002/acs.4480040610.
5. Р.Каллан. Основные концепции нейронных сетей. - М.: Изд. дом "Вильямс". 2001. –С. 289.
6. Новиков Ф.А. Дискретная математика для программистов. -СПб.: Питер. 2001. –С.304.
7. Golub D.N. and Gorban A.N. Multi-particle Networks for associative Memori, Proc. Jf the World congress on Neutral networks, Sept. 15-18, San Diego, CA, Lawrence Erlbaum Associates, 1996, pp. 772-775.
8. Чураков А.Л. Оптимальные и адаптивные системы: Учебное пособие для вузов. – М.: Энергоатомиздат, 1987.

9. Справочник по теории автоматического управления / Под ред. А.А. Красовского. -М.: Наука, 1987. - 712 с.
10. Igamberdiyev H., Yusupbekov A., Zaripov O., Sevinov J. Algorithms of adaptive identification of uncertain operated objects in dynamical models. Procedia Computer Science. Volume 120, 2017, Pages 854-861.
11. Бунич А.Л., Бахтадзе Н.Н. Синтез и применение дискретных систем управления с идентификатором / Отв. ред. В.А. Лотоцкий. М.: Наука, 2003. - 232 с.
12. Фомин В.Н. Методы управления линейными дискретными объектами. – Л.: Изд-во ЛГУ, 1985. -336 с.
13. Егупов Н.Д., Пупков К.А. Методы классической и современной теории автоматического управления. Учебник в 5 томах. - М.: Издательство МГТУ им.Н.Э.Баумана, 2004.
14. Amari Sh., Maginu K. Statistical Neuodinamics of Associative Memory // neurai Networks. 1988. V.1. N1. p.63-74.
15. Лютов А. Г., Платонова Д. Е. Интеллектуальное управление сложным технологическим процессом в условиях неопределенности // Тезисы докладов науч.-техн. конф. «Аэрокосмические технологии и образование на рубеже веков», Рыбинск, РГАТА, 2002.
16. Панченко Т.В. Генетические алгоритмы: учебное пособие / под ред. Ю.Ю.Тарасевича. – Астрахань: Издательский дом «Астраханский университет», 2007. – 87 с.

AUTHORS PROFILE

Zaripov Oripjon Olimovich doctor of technical sciences, professor Tashkent State Technical University named after Islam Karimov. A total of 250 scientific papers have been published. Of these, 3 monographs, 15 patents for the creation, 86 scientific articles, including 42 in national and 24 in foreign journals, were obtained. Direction of scientific activity: Automation of technological processes and production, information processing and management systems, E-mail: uz3121@gmail.com.

Sevinova Dildora Usmonovna, Assistant, Department of Mechatronics and robotics, Tashkent State Technical University named after Islam Karimov. A total of 3 scientific papers have been published. Of these, 1 patents for the creation, 2 scientific articles. Direction of scientific activity: Automation of technological processes and production, information processing and management systems.

Sevinov Iskandar Uchqun ogli, Magistrate, Department of Information processing and control systems, Tashkent State Technical University named after Islam Karimov. A total of 2 scientific papers have been published. Of these, 1 patents for the creation, 1 scientific articles. Direction of scientific activity: Automation of technological processes and production, information processing and management systems.